

Variations in urban traffic volumes

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This paper describes the variation in traffic volumes in the Dutch city of Almelo. For this study, we used traffic counts which were collected at about 20 intersections from September 2004 until September 2005. The objective of this study is to provide insight in both periodic and random variation in urban traffic volumes. This insight is used by policy makers and traffic managers to determine a suitable set of traffic measures. It is also a basis for short term predictions of volumes. We conclude that we can distinguish the following types of variation with respect to the average daily volume profile. (1) Seasonal variations with time-scales of weeks and weekly variations that describe the variation from day to day. These variations can be as large as 10% for the city of Almelo. (2) Periodic variations at time-scales of typically 30 minutes. These variations are recurrent and are often larger than 10%. (3) Noise. This variation has a random character. We show that the noise can be approximated by a Poisson distribution.

Keywords: reliability; flow; cluster; noise

1. Introduction

Congestion has been increasing worldwide for decades, but may be diminished if the capacity of the existing infrastructure is better utilised. Dynamic traffic management consists of a variety of measures to reach that goal. The collection of detailed information about travel demand is a necessary prerequisite for some of those measures. In general demand cannot be measured directly but must be estimated using information on volumes, i.e. traffic counts. For urban areas this information is becoming available in urban traffic information centres (e.g. Hasberg and Serwill, 2000; Kellerman and Schmid, 2000; Leitsch, 2002).

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When travel demand does not change significantly, e.g. as a result of new housing or offices, it is possible to forecast future travel demand with the use of historical data. Different approaches to forecast travel demand exist. For short term predictions traffic volumes are often extrapolated in time (e.g. Chrobok et al., 2004; Van Grol et al., 2000; Wild, 1997). For longer prediction horizons volume measurements can be matched to historical patterns. In these predictions neural networks (e.g. Yin et al., 2002; Dia, 2001) or clustering methods (e.g. Weijermars and Van Berkum, 2005; Chung, 2003) are used.

Travel demand patterns have been studied widely. Several factors contribute to variations in travel demand on different time-scales (e.g. Weijermars, 2007; Stathopoulos and Tsekeris, 2006). Some authors (e.g. Weijermars, 2007; Wild, 1997) found variations between different weekdays. This day-to-day variation is related to variations in activity patterns which can be quite significant in The Netherlands (e.g. Hilbers et al., 2004; Harms, 2003). Other examples of travel demand variations are seasonal variations (e.g. Li et al., 2006; Stathopoulos and Karlaftis, 2001b; Aunet, 2000), and weather related variations which are significant, but small when weather conditions are not extreme (e.g. Keay and Simmonds, 2005; Changnon, 1996). Because travel demand has got a spatial component, several authors have studied the relation between spatial and temporal variations. In general, weekly and seasonal patterns correlate with the type of location (e.g. Li et al., 2004; Schmidt, 1996; Faghri and Hua, 1995; Flaherty, 1993). The variations mentioned above are recurrent. They have time-scales which are significantly longer than the time-intervals (often 5 minutes) in which measurements are collected. These variations are therefore in theory predictable and we call these variations systematic. By studying these systematic variations we can provide policy makers and traffic managers with information about what will happen on the network in certain circumstances.

A comprehensive description of travel demand forms an important ingredient for the development of tools that can predict variations in urban flows. Unfortunately, little has been published about random variations or noise in urban volumes. Contrary to systematic variations (e.g. day-to-day, seasonal or weather related variations) these variations are not recurrent. In addition, the noise in different measurements is uncorrelated and these variations are therefore unpredictable. Without knowing the nature and amount of noise it is impossible to evaluate prediction models properly. For example, predictions based on extrapolation methods are much more sensitive to noise than predictions based on large sets of historical patterns. In addition, a small systematic increase in travel demand (related to the day of the week, the season or the weather situation) may lead to congestion, while as a result of the noise it might be unnoticed in the actual measurements.

The objective of this study is to provide insight in both periodic and random variation in urban traffic volumes. For this we used data which were collected at signalized intersections in the city of Almelo. In section 2 we describe the data. In section 3 we study systematic variations, which can occur on different time-scales. In section 4 we analyse the noise, which is separated from systematic variations. We discuss our results in section 5.

2. Data analysis

We studied traffic volumes in Almelo in The Netherlands. Data were collected at about 20 signalized urban intersections from September 2004 until September 2005. Vehicles were detected by means of inductive loop detectors. The data were processed into volume measurements per link per time interval. We define a volume profile $Q_d = (q_{1d}, \dots, q_{nd})$ as a time-series of n intervals for day d . In most cases measurements were provided in 5-minute intervals, so that $n = 288$. However, for about 30% of the links only measurements in 30-minute intervals were provided. For these links $n = 48$.

The volume measurements were inspected and invalid data were rejected by Weijermars and Van Berkum (2006). Invalid data are the result of errors in the measurements (e.g. by failures in the electronics or by miscounts in the number of passing cars). These errors were detected by using certain criteria (e.g. volumes should be equal or larger than 0, volumes should not exceed a certain maximum volume and 24 hour volumes should be larger than 0). Due to the malfunctioning of detectors during several days or even weeks, a significant fraction of the volume profiles was rejected. The remaining volume profiles are analysed in this study. We created a homogeneous sample with good statistics by only including links with at least 10 volume profiles per weekday (Monday, Tuesday, etc.). Our final sample consists of volume profiles of 72 intersection links (with a minimum of 50 profiles per link) of which 48 have 5 minute time-series. In this paper we study volume profiles for working days and for the school holiday period. We excluded the weekends and the public (national) holidays from the sample. In Figure 1 we show the study area. It should be noted that groups of links are on the same roads. Some of the results we find therefore implicitly include a spatial correlation between links.

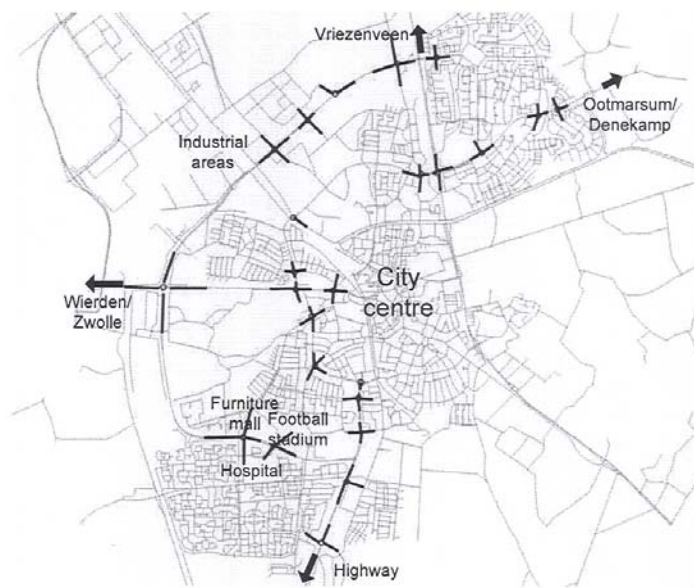


Figure 1. The city of Almelo.

Note: The thick lines correspond with intersection links for which traffic data were collected.

2.1 Clustering

To investigate volume variations in a systematic way, we grouped daily profiles in two ways. First, we used an unsupervised clustering method to cluster days with similar patterns. There are several statistical approaches for this type of clustering. For this sample we used the Ward hierarchical clustering procedure (Weijermars, 2007). Second, we classified daily patterns using different labels: day of the week (Monday, Tuesday, Wednesday, Thursday or Friday) and whether the day is part of the school holiday period or not. For example, all Monday profiles outside the holiday period belong to the same group.

2.2 Outliers

When traffic accidents, road works, or other unique events occur, traffic volumes can differ significantly from the average. The impact of these events on traffic circulation can be large. It is therefore important to identify these events as much as possible. Since our goal is to analyse regular variations, we want to detect and reject outliers from the sample. With the unsupervised cluster analysis described in the previous section outliers can be detected for each link. If a daily

profile deviates significantly from the average it will be clustered in a separate group (for details see Weijermars, 2007). In Figure 2 we show an example of a cluster containing outliers. In this example traffic was reduced significantly due to road works.

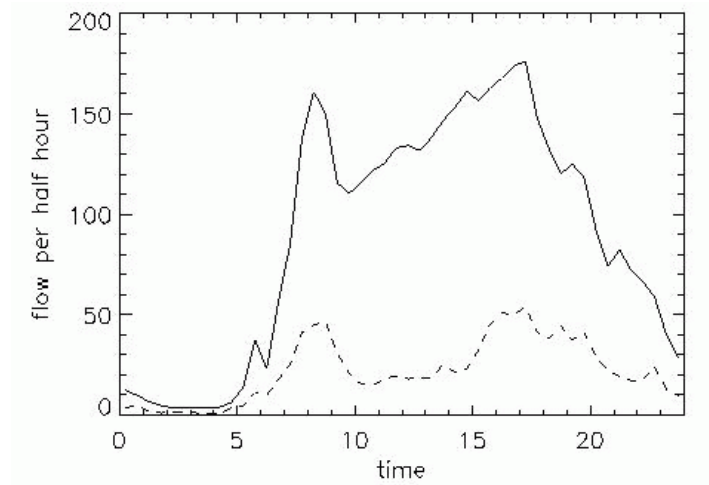


Figure 2. An example of an average volume profile for a cluster with normal profiles (solid line) and the average profile for a cluster with outlying volume profiles (dashed line)

Clustering is one of the methods for outlier mining (Weijermars, 2007). In this paper we used another method, a 3-sigma clipping criterion. First, we defined the distance $\Delta(R-S)$ between two profiles R and S as the root-mean-square (rms) of their differences per time interval.

$$\Delta(R-S) = \sqrt{\sum_{i=1}^n (R_i - S_i)^2 / n} \quad (1)$$

Per link we then determined the distances ΔQ_d between the daily profiles Q_d and the average (over all days) profile $\langle Q \rangle = (\langle q_1 \rangle, \dots, \langle q_n \rangle)$, with

$$\langle q_i \rangle = \sum_{d=1}^m q_{id} / m \quad (2)$$

where m is the number of days. Finally, we defined σ as the rms of the distances:

$$\sigma = \sqrt{\sum_{d=1}^m \Delta Q_d^2 / m} \quad (3)$$

When a distance ΔQ_d is larger than 3σ , the profile is identified as an outlier. With this criterion we found that approximately 3% of the sample are outliers. It is important to stress that with this criterion irregular measurements, e.g. caused by failing electronics, special events, accidents etc., can be selected, but that also noisy data may be selected by accident. We estimate that the latter fraction must be very small, because visual inspection of the data showed that the distribution of ΔQ_d is close to a normal distribution.

3. Systematic variations

Traffic counts show systematic variations in time. These variations can be caused by variations in travel demand or measurement errors. In section 2 we explained that we rejected data with (severe) measurement errors. Variations in travel demand consist of variations in trip generation,

trip distribution, the distribution of arrival and departure times, mode choice and route choice. These variations can have different causes, like for example congestion, changing weather conditions or road works.

In general, a daily pattern consists of two rush hour peaks, an off-peak period, an evening period and a night period. The strength and shape of these components depend on location (Weijermars, 2007), but also on the type of day and the season. With respect to a typical daily pattern, we thus observe day-to-day variation and seasonal variation. We discuss both variations in section 3.1. In section 3.2 we show that there are also significant short term variations in traffic volumes, which have time-scales less than an hour.

3.1 Day-to-day variation and seasonal variation

Several authors (e.g. Wild, 1997; Van Grol et al., 2000) found that the shape of a volume profile depends on the day of the week. For Almelo, day-to-day variations were detected by unsupervised clustering. In general clustering yields two to four clusters. In most cases weekdays, the school holiday period and / or road works are on the basis of these clusters. For a more extensive discussion of the analysis of urban traffic patterns by means of clustering, we refer to Weijermars (2007).

In Figure 3 we illustrate the day-to-day variations. In this figure we show the relative difference between the mean profile for each group of days and the mean profile averaged over all days. The different groups are Mondays, Tuesdays, Wednesdays, Thursdays, Fridays and the school holiday period. For the working days we used profiles outside the school holiday period. From Figure 3 we can conclude the following. Mondays and Fridays show a low and high off-peak respectively. On Thursdays there is extra traffic around 20h (due to shopping), and on Friday evening there is significant more traffic which is related to social activities. As expected, travel demand is significant lower during the holiday period, especially during the morning rush hour. Differences between working day rush hours may be smaller, but are still significant. In particular, on Friday there is between 5 and 10% less travel demand during rush hour than on other working days. It is worth mentioning that similar patterns have been found for the area in Amsterdam Southeast (Houtriet, 2007).

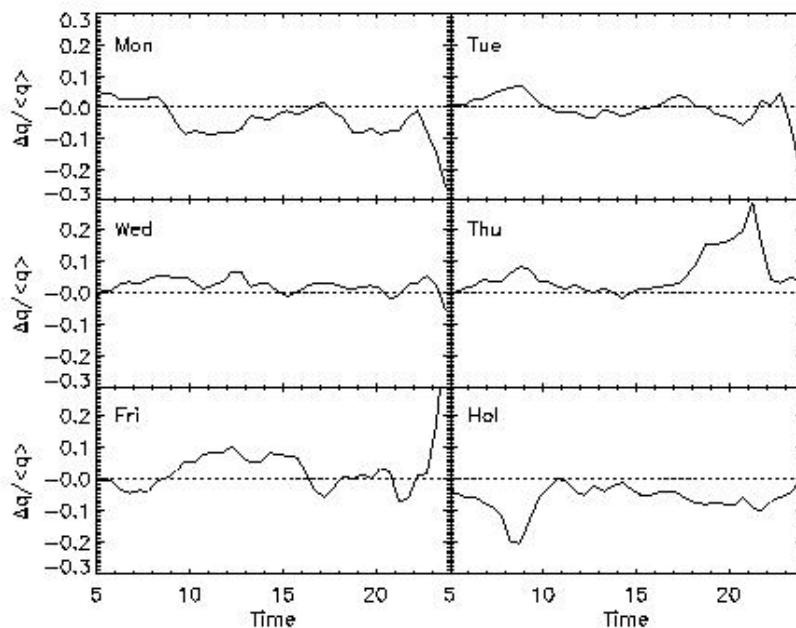


Figure 3. The relative difference between the mean profile per group and the mean profile over all groups. The groups are: Mondays (top left), Tuesdays (top right), Wednesdays (center left), Thursdays (center right), Fridays (bottom left) and Holidays (bottom right). The figure shows network averages.

Seasonal variation has been studied in different areas (e.g. Aunet, 2000; Stathopoulos and Karlaftis, 2001b). Seasonal patterns can be used to estimate the annual average daily traffic (AADT) volume for locations where there is only a limited amount of data available (e.g. Zhao and Chung, 2001; Granato, 1998). We estimated the seasonal variation by the seasonal index, which is the ratio between the average weekly volumes and the annual average. In Figure 4 we show the seasonal index for Almelo. This is done for the following three intervals: 6-10h (morning rush hour), 10-15h (off-peak) and 15-19h (evening rush hour). Figure 4 shows that the seasonal index has got quite similar patterns for the different time intervals. The travel demand reaches its maximum during spring, while summer and winter are relatively quiet. There is approximately 10% less traffic in the quiet period than during the most busy period. In this analysis we excluded the school holiday period, so that the summer period only has got a few measurements.

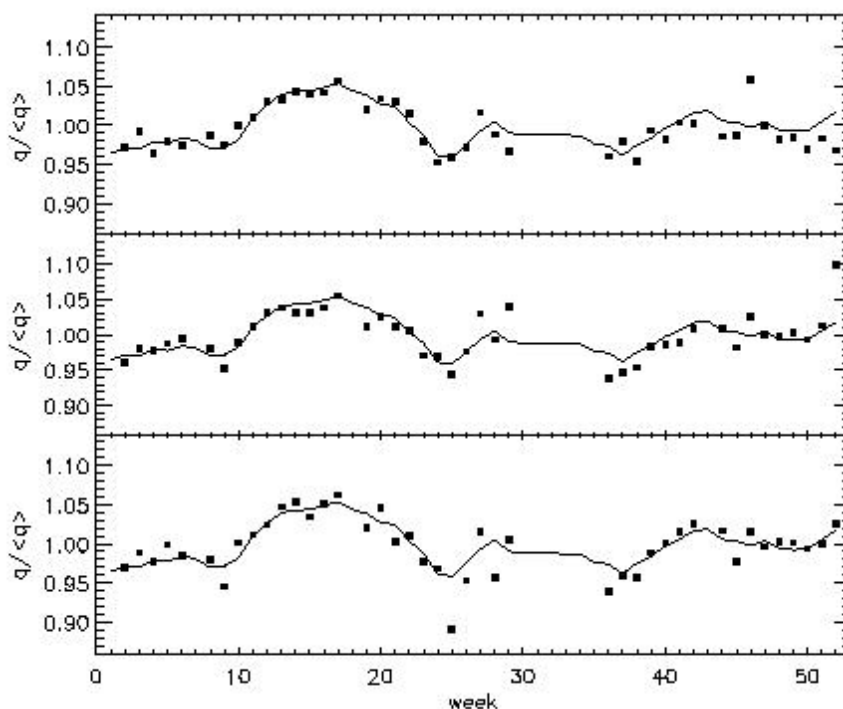


Figure 4. The seasonal index, defined as the ratio between the average weekly volume and the annual average, for the morning rush hour (top), the off-peak (centre) and the evening rush-hour (bottom). The solid line represents the smoothed seasonal index for the average daily traffic volumes. The figure shows network averages.

We also studied the seasonal variation at a link level. We looked at the daily residuals, which are the relative differences between the daily volumes and the annual average daily volume (for each group of days). In Figure 5 the daily residuals for successive working days are shown for all links. Figure 5 shows that the residuals can be as large as 20%. The figure shows that there is a strong correlation between the residuals of successive working days. This correlation implies that there is a strong seasonal variation, because the variation between successive working days is much smaller than the total variation.

Different cultural and social circumstances make it difficult to compare our results with results from other countries. In Wisconsin (USA) seasonal variations are about 13% in urban areas (Aunet, 2000). This is quite comparable with the amount of variation we find. However, in Wisconsin the peak in travel demand is in summer, while in Almelo and in Athens (Stathopoulos and Karlaftis, 2001b) the summer period shows a dip in travel demand. The reasons for seasonal

variations are also not always clear. For a more detailed description of possible causes of seasonal variations we refer to Weijermars (2007).

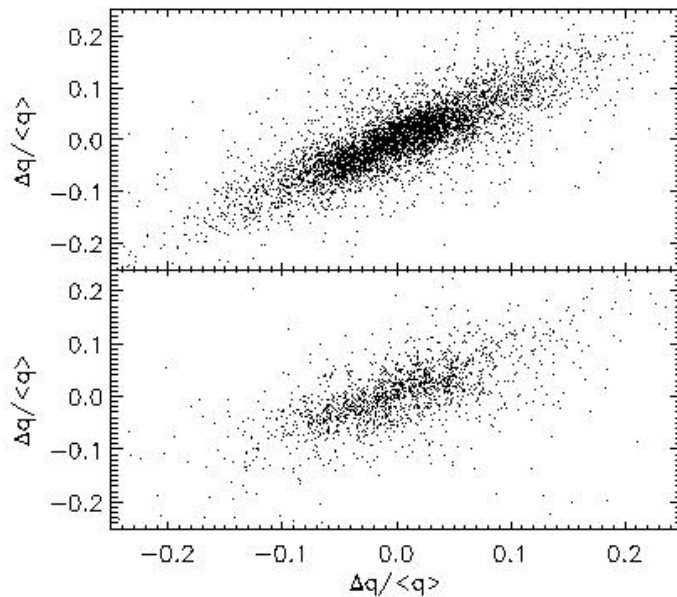


Figure 5. Daily residuals, which are the relative differences with respect to the annual average (for each group of days), for successive working days.

In the top panel the successive working days are also successive week days, while in the bottom panel the days are not successive, i.e. weekends are in between them.

3.2 Short term variations

Relatively little has been published about short term variations. Stathopoulos and Karlaftis (2001a) did a spectral analysis of time-series in Athens, and found evidence for some systematic short term variations. In this study we also looked for short term variations that have a recurrent character. In the left panel of Figure 6 we show 5 minute volume profiles, which are averages over all working days. We show mean profiles for the network average, for an individual link with significant short term variations and for a link with relatively little short term variations. According to the figure, two characteristic features are rather common. First, oscillations occur on time-scales smaller than one hour. Secondly, multiple peaks with amplitudes up to 20% can be identified during the rush hour. Note that the number of averaged profiles in Figure 6 is large enough (more than 100 on average) to reduce the noise levels significantly. The contribution of noise in the average profiles is therefore negligible.

Because short term variations can be significant, we are interested in the frequencies at which they occur. For this purpose we took the Fourier transform of the volume time-series. We show the power spectrum (logarithmic scale) of the transformed profiles in the right panel of Figure 6. The figure shows peaks around frequencies that correspond with respectively 30 and 15 minute periods (from left to right). From a visual inspection we found dips in the volumes around the whole and the half hours. It is worth stressing that we found these results throughout the network, and that similar results were found in the city of Amsterdam (Houtriet, 2007). A possible explanation for these oscillations in travel demand is the fact that society is regulated by 30 (and to a lesser extend 15) minute periods, i.e. many people have appointments that start at the half hour.

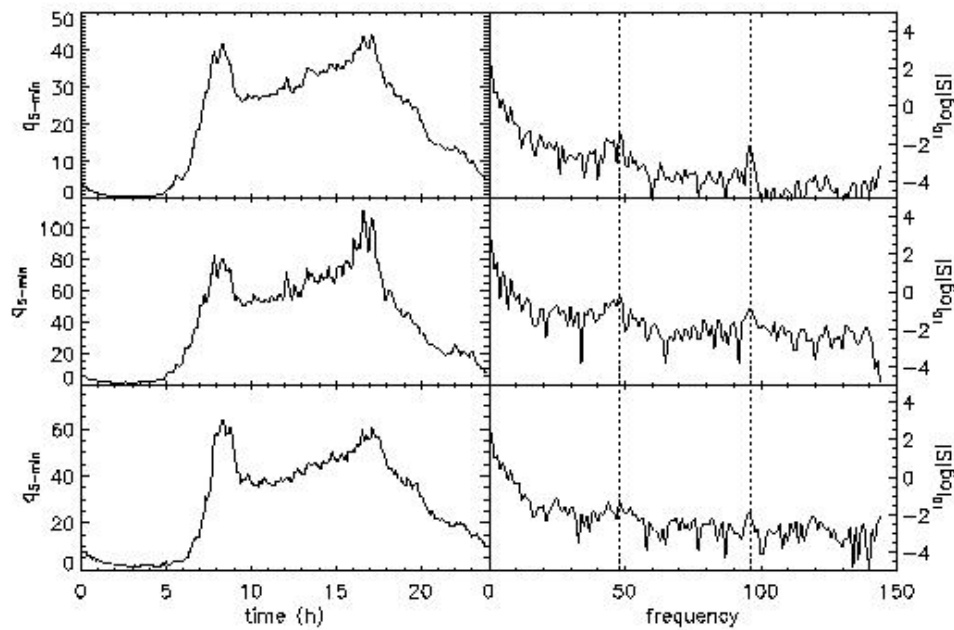


Figure 6. Short term variations in travel demand.

Examples of profiles (left) and their Fourier power spectra (right). The dotted lines in the right panel correspond with 30 (left) and 15 minute periods (right) respectively. The examples are: the average profile for the whole network (upper panel) and average profiles for links with significant short term variations (centre panel) and with relatively little short term variations (bottom panel).

4. Noise

In the previous section we described different systematic variations which occur in volume measurements. However, when traffic volume time-series are inspected by eye, it immediately stands out that a large amount of the variation between successive time-intervals looks random. Contrary to recurrent variations or slow changing systematic variations we call this variation noise. The amount of noise is an important quantity. If the amount of noise increases, systematic variations can be detected less easily. It also gives an under limit for the quality of short term predictions, because noise cannot be predicted by definition. Noise can be caused by the random arrival process of cars. This process results in different headways between following cars, which is an important source of variation on highways. In urban areas traffic flows may be interrupted by traffic signals, which refract the random process. However, variable and unknown green times add to quasi-random variations. In practice, all variations which have short time-scales and which do not follow a recurrent pattern can be considered as noise. Note that random miscounts in the measurements also contribute to the noise.

A measurement q thus can be described in the following terms:

$$q = \langle q \rangle + \varepsilon + \nu \quad (4)$$

with $\langle q \rangle$ the average volume (for a group of days), ε the systematic variation and ν the noise.

Systematic variations in successive measurements are strongly correlated, because these variations have time-scales that in general are longer than the time-intervals of the measurements. We assume that this correlation $\rho(\varepsilon_i, \varepsilon_{i+1}) \sim 1$. This implies that the relative systematic variation c is constant within a certain time-interval. In that case, the variance in ε , $\text{var}(\varepsilon) = (c \langle q \rangle)^2$.

The most important characteristic of noise is that the noise in different measurements is uncorrelated, so that $\rho(v_i, v_j) = 0$ for $i \neq j$. This implies that the variance of the total noise in the sum of measurements is equal to the sum of the variances in single measurements. The total volume is proportional to the number of measurements (each measurement within a fixed time-interval). Thus, notwithstanding the complicated processes behind the noise, the variance in the noise is proportional to the expected volume. In fact, we assume that $\langle q \rangle + v$ is Poisson distributed. In that case, the variance in v , $\text{var}(v) = \langle q \rangle$.

Because the noise and the systematic variations are uncorrelated, both their variances add up, so that

$$ms(\Delta q_d) = \text{var}(v) + \text{var}(\varepsilon) = \langle q \rangle + c^2 \langle q \rangle^2 \quad (5)$$

or

$$\frac{ms(\Delta q_d)}{\langle q \rangle} = 1 + c^2 \langle q \rangle \quad (6)$$

with $ms(\Delta q_d)$ the total variance which is estimated by the mean square of the residuals $\Delta q_d (=q_d - \langle q \rangle)$. For each time interval and link, we determined the residuals. We did this for profiles with 5 minute time lags, but also for aggregated time-series with time lags of respectively 10, 30 and 180 minutes.

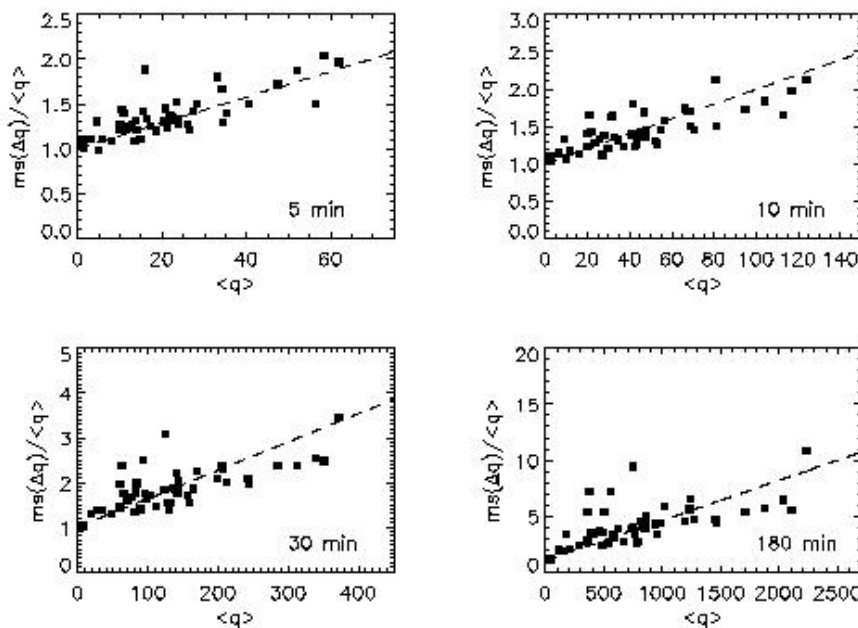


Figure 7. The relation between noise and systematic variations.

The y value should be equal to 1 when all the variation is Poisson noise. The slope of the dashed line therefore gives an indication for the average relative systematic variation. Results are shown for 5 minute (top left), 10 minute (top right), 30 minute (bottom left) and 180 minute time-series (bottom right). The symbols represent link values. The dashed lines are eye-ball fits through the measurements.

Equations (5) and (6) show that for small volumes the noise dominates, while for large volumes systematic variations may dominate. In other words, for increasing volumes the noise averages out, while systematic variations do not. In Figure 7 we have plotted the left hand side of equation (6) versus $\langle q \rangle$ for each link (averaging over all time-intervals). From Figure 7 we conclude that the link values follow equation (6) quite well. This is shown by the lines in Figure 7, which were

fitted by eye. An alternative would have been to apply a standard linear regression method. However, in that case weights should be assigned to all data points. We did not choose this type of regression because we are unaware of the weights, and a choice for equal weights might produce wrong results. This is also indicated by the scatter in Figure 7. Some links lie quite above the trend. This might be explained by large systematic variations (larger than average), due to for example road works or events which were not identified as outlying.

The assumption that the noise can be approximated by a Poisson distribution seems valid, because the y-values in the figure are approximately 1 for links with small volumes. At first sight, the noise appears quite small, especially since the cycle periods of traffic lights are unknown and thus contribute to the noise. On the other hand, traffic signals refract the random arrival process. Thus, although urban traffic flows cannot be described by a random Poisson process the Poisson statistics appear to be a good description for the noise. However, it is plausible that the number of traffic signal cycles per time lag decreases towards intersections that serve high volumes. In that case, some of the variation that is now contributed to the systematic variation, actually is caused by the variation in traffic signal cycles. This could explain the sharp decrease in the average relative systematic variation c (square root of the slopes in Figure 7) from 12% for 5 minute time-series to 8% and 6% for 30 and 180 minute time-series respectively. We therefore argue that the variance from a Poisson distribution probably gives an under limit for the amount of noise.

In Figure 8 we summarise our results by showing the mean relative variations as function of the time of the day. The mean relative variation is given by the relative root mean square (rrms) of the residuals. Figure 8 shows that the variation is very large if no clusters or groups are defined. The variation within clusters is smaller than that within classified groups, but the smallest variations are found in classified groups for which seasonal variations (i.e. the correlation between variations of successive days from Figure 5) have been taken into account. In all cases, the variations are larger than the Poisson noise, which is an under limit of the variation. We conclude that, in general, day-to-day and seasonal variations can explain most of the total systematic variation.

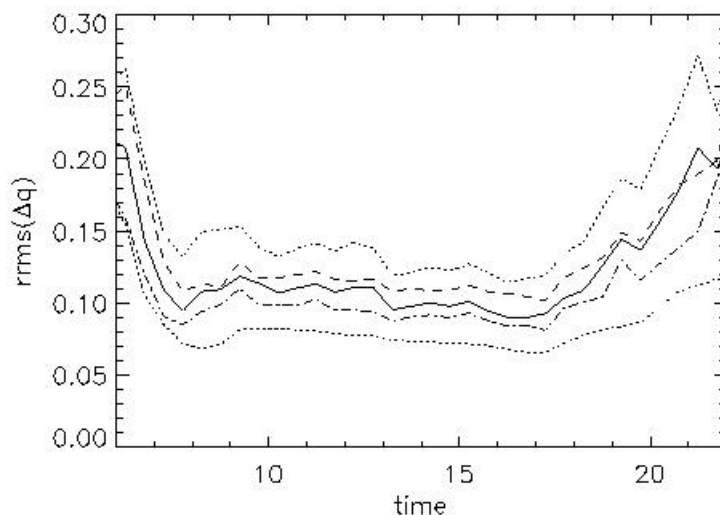


Figure 8. The relative root mean square of volume residuals with respect to link averages (dotted line at the top), within classified groups (dashed line), within clusters (solid line), within classified groups for which seasonal variations have been taken into account (dashed dotted line), and the rrms of the noise (dotted line at the bottom)

5. Discussion

For about 70 links at about 20 intersections in Almelo we obtained traffic volume profiles observed between September 2004 and September 2005. We studied both random and systematic variations in traffic volumes.

Per link, daily volume profiles were clustered by an unsupervised Hierarchical Ward clustering algorithm. Abnormal daily flow profiles, which are caused by eventualities like accidents and road works, were identified and rejected from the sample. In future work we will examine the characteristics of these profiles in more detail.

We showed that both short term and long term systematic periodic variations occur in travel demand. On short time-scales volumes can change significantly (up to 20%) both during rush hour and during the off-peak. These variations typically have periods of 30 (and to a lesser extend 15) minutes, which we explain by the fact that society runs on half hour intervals. For time-scales longer than a day periodic variations between different week days and between holidays and non holidays can exceed the 10%. Seasonal variations in travel demand can also be as large as 10% (network wide).

We conclude that the noise can be approximated by a Poisson distributed, although this probably gives an under limit. If we take the noise into account, we find that day-to-day and seasonal variations can explain most of the total systematic variation. Understanding random and systematic variations is important for several reasons. Local government officials require clear information about travel demand patterns upon which they can act using their specific local knowledge of the area. More generally, knowledge about random and systematic variations are essential for reliable travel demand predictions. Travel demand predictions can be used in predictions of traffic flows using macroscopic or microscopic models (e.g. Esser and Schreckenberg, 1997) and in the development of traffic signal control plans (e.g. Yang et al., 2005; Yang, 2004).

It is worth mentioning that congestion is negligible in Almelo. Therefore travel demand can be measured by traffic counts. However, in congested areas traffic volumes are a measure for capacity rather than travel demand. In future work we want to study to what extend we can estimate travel demand from traffic counts in congested areas.

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References

- Aunet, B. (2000). Wisconsin's approach to variation in traffic data. Paper presented at the *North American Travel Monitoring Exhibition and Conference 2000*, Wisconsin.
- Changnon, S.A. (1996). Effects of summer precipitation on urban transportation. *Climate Change*, vol. 32, pp. 481-494.
- Chrobok, R., Kaumann, O., Wahle, J. and Schreckenberg, M. (2004). Different methods of traffic forecasting based on real data. *European Journal of Operational Research*, vol. 155, pp. 558-568.
- Chung, E. (2003). Classification of traffic pattern. Paper presented at the *10th World Congress on Intelligent Transport Systems 2003*, Madrid.

- Dia, H. (2001). An object-oriented neural network approach to short-term traffic forecasting. *European Journal of Operational Research*, vol. 131, pp. 253-261.
- Esser, J. and Schreckenberg, M. (1997). Microscopic simulation of urban traffic based on cellular automata. *International Journal of Modern Physics C*, vol. 8, no. 5, pp. 1025-1036.
- Faghri, A. and Hua, J. (1995). Roadway seasonal classification using neural networks. *Journal of Computing in Civil Engineering*, vol. 9, no. 3, pp. 209-215.
- Flaherty, J. (1993). Cluster analysis of Arizona automatic traffic recorder data. *The Science of the Total Environment*, vol. 1410, pp. 93-99.
- Granato, S. (1998). The impact of factoring traffic counts for daily and monthly variation in reducing sample counting error. Paper presented at the *Transportation Conference Proceedings 1998*, Iowa.
- Harms, L. (2003). Mobiel in de tijd, op weg naar een auto-afhankelijke maatschappij 1975-2000 (in Dutch). Technical report, 2003, Sociaal en Cultureel Planbureau, The Netherlands.
- Hasberg, P. and Serwill, D. (2000). Stadtfoköln – a global mobility information system for the Cologne area. Paper presented at the *7th World Congress on Intelligent Transport Systems 2000*, Turin.
- Hilbers, H., Van Eck, J. R. and Snellen, D. (2004). Behalve de dagelijkse files, over betrouwbaarheid van reistijd (in Dutch). NAI uitgevers, 2004, Ruimtelijk Planbureau, The Netherlands.
- Houtriet, E. (2007). Monitoring Amsterdam Zuidoost: Het analyseren van VRI detectielus data (in Dutch). Msc thesis, University of Twente.
- Keay, K. and Simmonds, I. (2005). The association of rainfall and other weather variables with road traffic volume in Melbourne, Australia. *Accident Analysis and Prevention*, vol. 37, pp.109-124.
- Kellerman, A. and Schmid, A. (2000). Mobinet: Intermodal traffic management in Munich –control centre development. Paper presented at the *7th World Congress on Intelligent Transport Systems 2000*, Turin.
- Leitsch, B. (2002). A Public-private partnership for mobility – Traffic management Center Berlin. Paper presented at the *9th World Congress on Intelligent Transport Systems 2002*, Chicago.
- Li, M.T., Zhao, F. and Wu, Y. (2004). Application of regression analysis for identifying factors that affect seasonal traffic fluctuations in Southeast Florida. *Transportation Research Record*, vol. 1870, pp. 153-161.
- Li, M.T., Zhao, F. and Chow, L.F. (2006). Assignment of seasonal factor categories to urban coverage count stations using a fuzzy decision tree. *Journal of Transportation Engineering*, vol. 132, pp. 654-662.
- May, A. (1990). *Traffic Flow Fundamentals*. Prentice-Hall Inc., New Jersey.
- Schmidt, G. (1996). Hochrechnungsfactoren für Kurzzeitzählungen auf Innerortstrassen. *Strassenverkehrstechnik*, vol. 40, no. 11, pp. 546-556.
- Stathopoulos, A. and Karlaftis, M.G. (2001a). Spectral and cross-spectral analysis of urban traffic flows. Paper presented at the *4th IEEE Conference on Intelligent Transportation Systems 2001*, Oakland.
- Stathopoulos, A. and Karlaftis, M.G. (2001b). Temporal and spatial variations of real-time data in urban areas. *Transportation Research Record*, vol. 1768, pp. 135-140.
- Stathopoulos, A. and Tsekeris, T. (2006). Methodology for processing archived ITS data for reliability analysis in urban networks. *Intelligent Transport Systems*, vol. 153, no. 1, pp. 105-112.
- Van Grol, R., Inaudi, D., Kroes, E. (2000). On-line traffic condition forecasting using on-line measurements and a historical database. Paper presented at the *7th World Congress on Intelligent Transport Systems 2000*, Turin.
- Weijermars, W.A.M. and Van Berkum, E.C. (2005). Analyzing highway flow patterns using cluster analysis. Paper presented at the *8th IEEE conference on Intelligent Transportation Systems Conference 2005*, Vienna.

Weijermars, W.A.M. and Van Berkum, E.C. (2006). Detection of invalid loop detector data in urban areas. *Transportation Research Record*, vol. 1945, pp. 82-88.

Weijermars, W.A.M. (2007). *Analysis of urban traffic patterns using clustering*. Ph.D. thesis, University of Twente.

Wild, D. (1997). Short-term forecasting based on a transformation and classification of traffic volume time series. *International Journal of Forecasting*, vol. 13, pp. 63-72.

Yin, H., Wong, S.C., Xu, J. and Wong, C.K. (2002). Urban traffic flow prediction using a fuzzy-neural approach. *Transportation Research Part C*, vol. 10, pp. 85-98.

Yang, J.S. (2004). Traffic Signal Timing Control for a Small-scale Road Network. *Control and Applications*, vol. 441, pp. 48-49.

Yang, Z.S., Chen, X., Tang, Y.S. and Sun J.P. (2005). Intelligent Cooperation Control of Urban Traffic Networks. Paper presented at the 4th *International Conference on Machine Learning and Cybernetics 2005*, Guangzhou.

Zhao, F. and Chung, S. (2001). Estimation of annual average daily traffic in a Florida county using GIS and regression. *Transport Research Record*, vol. 1769, pp. 113-122.